# Job Search: Empirical Applications[1]

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[1] Slides adapted from those made by Bart Cockx and Marc Gurgand.

# Outline

1. Introduction
2. Basic Concepts: Hazard rate and Survivor function
3. Estimation
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   - Non-parametric estimation
   - Parametric models
4. Unobserved heterogeneity and duration dependence
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# Introduction

Job-search theory generates predictions about the determinants of

- The reservation wage (the acceptance rate) and of
- Job-search effort,

$\Rightarrow$ Clear-cut effect on exit rates out of unemployment.

There is a relatively large consensus on these theoretical predictions.

Examples:

- Higher benefits $\rightarrow$ lower exit rate out of *insured* unemployment.
- A social norm in a sub-population generating a stigma if jobless has the opposite effect.
- Increasing (resp., lowering) the marginal cost (resp., return) of job-search effort $\rightarrow$ lowers effort. Having young kids or a poor knowledge of the local language are plausible reasons.
- (...)

(Some theoretical predictions are also not clear-cut [e.g. impact of an improvement in business cycle conditions])

*Can the clear-cut theoretical predictions easily be confronted to the data?*

No. Why?

- What type of information is observable? Is it reliable?
- How can the observed information be exploited?

Information about **self-reported** reservation wages is mainly collected through surveys.

One can raise doubts about the quality of this information.

Acceptance decisions are typically unobserved.

About job-search effort,

- How to measure it? Various indicators are possible. For an implementation, see Della Vigna, Hieing, Schmieder and Trenkle (2021).
- Again typically self-reported. Baker and Fradkin (2017) and Marinescu and Skandalis (2021) are counter-examples.

Individual data on

- The **duration** spent in unemployment
- The destination state (e.g. employment vs inactivity)

are

- More widespread and
- More reliable, in particular when administrative data are used (instead of survey data).

$\rightarrow$ The focus of these slides: How to exploit **duration data**?

The analysis of the *duration* spent in a specific state[2] requires specific (relatively complex!) tools. These slides introduce them.
= Tools first used in biostatistics.
A quite specific vocabulary is used!

[2] Unemployment, being alive, length of existence of a firm, duration of strike,...

# Reduced Form vs Structural Approaches

Job-search theory $\Rightarrow$ A formula for the exit rate out of unemployment.

**1. Structural approach**

Meaning: The theory about optimal behavior of the job-seeker
= A strict guide to specify the model.

Example: According to the *basic job-search model* developed in a stationary environment and a continuous time setting, the *hazard rate* (or exit rate out of unemployment) $\phi$ verifies

$$\phi(x) \equiv \lambda \overline{H}(x), \quad \text{where} \quad \overline{H}(x) \equiv 1 - H(x) \tag{1}$$

where $x$ is the optimally chosen reservation wage.

Assuming a certain parametric specification for the CDF $H$, the "structural parameters" are these parameters and $\{z, q, \lambda, r\}$.

- $\oplus$ Aim of the "structural approach" = to estimated these "structural parameters" which have a clear economic interpretation.
- $\ominus$ But if theory simplifies reality too much
  $\Rightarrow$ Too much structure imposed $\Rightarrow$ biased estimations.

## 2. Reduced form approach

- ⊕ More flexible since it does not impose the complete theoretical structure of the model.
- Simply check whether the comparative static predictions of theory are consistent with the empirical observations.
- ⊖ In general, estimated parameters cannot unambiguously be related to the “structural parameters”:
  “Reduced-form analysis cannot separate between the relative magnitudes of the job offer arrival rate and the acceptance probability, or estimate the relative magnitude of the effects of the $X$ variables [= the individual characteristics] on them.” (Eckstein and van den Berg, 2007)

The reduced form approach is more often used than the structural one.

An illustration (Lalive, van Ours and Zweimüller, 2006) will follow.

# Broader motivation?

In addition, decision makers and citizens typically view unemployment as detrimental.
They would like to have answers to a broad set of questions concerning the determinants of **unemployment duration**:

- Individual characteristics (skill level, geographical location,...) detrimental to a rapid exit to a job?
- The role of job-search channels?
- The role of social networks?
- The impact of the design of unemployment insurance schemes and other policies developed by the public/private employment services?
- The role of unemployment duration *per se* on the exit rate?
- ...

+ Interest in characteristics of the job (type of contract, earnings,...)

# Basic Concepts for the Analysis of Duration

"**Competing risks models**" (= several types of events occur):
When one considers unemployment with *more then one* possible destination state
Examples of destinations:

- Employment,
- Taking part to an "active labor market policy" (e.g. a training scheme),
- Withdrawal from the labor force.

These slides introduces to "**single risk**" models only (i.e. a single destination).
*The notions introduced here can be generalized to competing risks models.*

The following slides are only partly covered by p. 286-295 of Cahuc, Carcillo and Zylberberg (2014) ('CCZ').
Additional references:
For more information, see e.g. Lancaster (1990), van den Berg (2001) and Chap. 17 and 18 of Cameron and Triverdi (2005).

# The hazard rate

Aim = To express the *hazard rate* (or exit rate) in full generality in a continuous time setting. The environment can be *non*-stationary.

Let $t$ be a realization of the random duration in unemployment $T$.

Consider a very small interval of time $[t, t+\Delta]$. The *unconditional* probability of leaving unemployment to employment during this small interval of time, Prob $(t \leq T < t+\Delta)$, verifies:

$$\text{Prob } (t \leq T < t+\Delta) = \text{Prob } (t \leq T < t+\Delta \mid T \geq t) \cdot \text{Prob}(T \geq t)$$

where the first term on the right-hand-side is the probability of the same event *conditional* on staying ("**surviving**") in unemployment until the beginning of the t$^{th}$ interval.

For $\Delta$ small enough, this *conditional* probability can be written $\phi(t).\Delta$

So,

$$\phi(t) = \frac{\text{Prob } (t \leq T < t + \Delta)/\Delta}{P(T \geq t)}, \tag{2}$$

The **hazard rate** $h(t)$ out of unemployment is defined as the following limit:

$$h(t) = \lim_{\Delta \to 0} \phi(t) = \frac{g(t)}{1 - G(t)} \tag{3}$$

where

- $g(t) = \lim_{\Delta \to 0} \frac{\text{Prob } (t \leq T < t + \Delta)}{\Delta}$ is the density function of $T$ evaluated at $t$;
- $G(t) = \text{Prob}\,(T \leq t)$ is the cumulated density function 'CDF' (or distribution function) of $T$ evaluated at $t$.

Expression (3) shows the link between the hazard rate, the density function and the distribution function of unemployment duration.

We wish to see how this hazard rate relates to *observations* on unemployment duration $\Rightarrow$ Invert (3) to get the CDF of duration, $G$.

Let $\overline{G} \equiv 1 - G(t)$ be the "**survivor function**" (or "survival function"), i.e. the probability that the unemployment duration $T$ exceeds $t$.

$$h(t) = \frac{g(t)}{\overline{G}(t)} = -\frac{d \ln \overline{G}(t)}{dt} \tag{4}$$

which is a differential equation: $d \ln \overline{G}(t)/dt = -h(t)$.

One can easily solve this differential equation by multiplying both sides of (4) by $(-dt)$ and by taking integrals between $T = 0$ and $T = s$ for any $s$:

$$-\int_0^s h(t)dt = \int_0^s d \ln \overline{G}(t) = \ln \overline{G}(s) - \ln \overline{G}(0) = \ln \overline{G}(s) \tag{5}$$

So,

$$\overline{G}(s) = \exp\left[-\int_0^s h(t)dt\right]. \tag{6}$$

where $\int_0^s h(t)dt$ is called the "**integrated hazard**".
Expression (6) defines the "survivor" $\overline{G}$ as a function of the current *and* past hazard rates.

Consequently, the CDF and the density functions of duration $T$ are related to the hazard function by:

$$G(s) = 1 - \exp\left[-\int_0^s h(t)dt\right] \tag{7}$$

$$g(s) = \frac{dG(s)}{ds} = h(s)\exp\left[-\int_0^s h(t)dt\right] \tag{8}$$

These are the basic ingredients of a likelihood function (see below).

## Exercise (1)

*Check that if the hazard is constant, i.e. if* $h(t) = \phi$ *defined in (1), one has* $E(T) = \int_0^{+\infty} \overline{G}(s)ds = \frac{1}{\phi}$.
*Hint: Use Integration by parts and L'Hospital's rule.*

## Exercise (2)

*The Weibull specification of the hazard being*

$$h(t) = \gamma\alpha t^{\alpha-1}, \;\; \gamma > 0, 0 < \alpha \lesseqgtr 1$$

- *Study the profile of* $t \in (0, +\infty) \mapsto h(t) \in \mathbb{R}^+$
- *Check that the survivor function is given by* $\overline{G}(s) = \exp[-\gamma s^{\alpha}]$

*Note: The Weibull specification is simple but not flexible enough*

# Equivalent notions when data are discrete

- Exits cannot occur before $t_1$
- Exits can take place at discrete points in time $t_1, t_2, ..., t_j, ...$

Hazard:

$$\phi(t_j) = P(T = t_j \mid T \geq t_j) \tag{9}$$

Survival:

$$\overline{G}(t) = P(T > t) = \prod_{t_j \leq t} \left(1 - \phi(t_j)\right) \tag{10}$$

Example : $\overline{G}(t_2)$:

$$P(T > t_2) = P(T > t_2 \mid T > t_1)P(T > t_1)$$

$$P(T > t_1) = 1 - P(T = t_1) = 1 - \phi(t_1)$$

No exit at $t_2$ given no exit at $t_1$: $P(T > t_2 \mid T > t_1) = 1 - P(T = t_2 \mid T > t_1) = 1 - P(T = t_2 \mid T \geq t_2) = 1 - \phi(t_2)$

# Estimation of duration models

# Censoring

**Censoring** means "incomplete observation". It is assumed that the process of censoring is independent from the process of interest (unemployment duration).

Some important types of censoring:

An observation period is by definition of finite length. Consequently,

(1) Some spells are already ongoing at the beginning of the observation period: these spells are said to be "left censored".

(2) some spells might not have ended before the end of the observation period: "right censored" spells.

**Calendar time ($\tau$) and duration ($t$) are two different measures.**
Let $\tau_0$ (resp., $\tau_1$) be the (calendar) time at which observation starts (resp., ends):

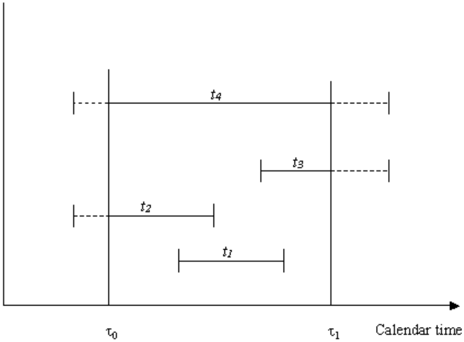


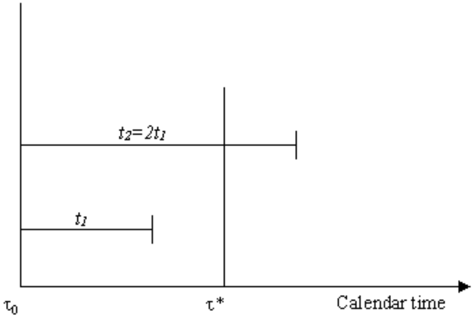

Figure: Four example of individual trajectories

1. Spell 1 is a "**completed spell**" within the observation period
2. Spell 2 is a "**left-censored**" spell
3. Spell 3 is a "**right-censored**" spell
4. Spell 4 is both "left and right-censored".

Sampling of data: A Major distinction:

- "Flow sampling": a (random) sample of fresh spells is followed through time (people observed as of the start of their spell)
- "Stock sampling": a (random) sample in the stock of people occupying a given position (say, unemployment); one only observes and follows people that are in the stock at the sampling date.

$\diamondsuit$ *Stock samples* face the problem of "**length bias**" even if one has information on the date at which the spells started.
To see this, consider 2 spells, each beginning at the same date, but the second spell lasts twice as long as the first one : $t_2 = 2t_1$.
$\tau_0 =$ the starting date of both spells
$\tau^* =$ the time at which the researcher samples spells.




It can be seen that the first spell cannot be observed at $\tau^*$, clearly because it does not last long enough. This is a general phenomenon. For, suppose that one shifts the sampling date $\tau^*$ gradually from $\tau_0$ to $(\tau_0 + t_2)$, then it is clear from the figure that the long spell will be sampled twice as much as the shorter spell, because it is twice as long.

◊ Right censoring is always present:
(i) In the case of a *cross-section* (a census or a sample), at the date of observation, the unemployment spells are incomplete (i.e. right-censored).

(ii) When a sample is followed (say, in unemployment), the period of observation stops at some point in time.
$\Rightarrow$ Here also, some spells will be right-censored.

In both cases, there is an "**interruption bias**".

◊ Take-home messages

1. Whether the length or the interruption bias dominates is an open question.
   But the bias can be very important.
2. As far as possible, limit the analysis of duration to *flow samples* (where only right-censoring is present and easy to handle).

# Non-parametric estimation

= A *descriptive* approach (no explanatory variables; with censoring).
Assumptions:

- Exits (say, to a job) cannot occur before $t_1$
- Exits can take place at discrete points in time $t_1, t_2, ..., t_j, ...$
- A flow sample of $N$ unemployment spells
- Number of spells ending at $t_j$: $d_j$
- Number of spells censored at $t_j$: $m_j$
  Reasons of censoring: random disappearance from the sample, exit to another destination than a job, such as retirement.
- Censoring is a process independent of unemployment duration

The number of spells that can possibly end at $t_j$ (the "risk set") is:

$$r_j = N - \sum_{k<j} (d_k + m_k)$$

Hazard estimation:

$$\hat{\phi}(t_j) = d_j / r_j \tag{11}$$

# Survival estimation ("Kaplan-Meier" estimation)

$$\hat{\bar{G}}(t) = \prod_{t_j \leq t} \left(1 - \frac{d_j}{r_j}\right) \tag{12}$$

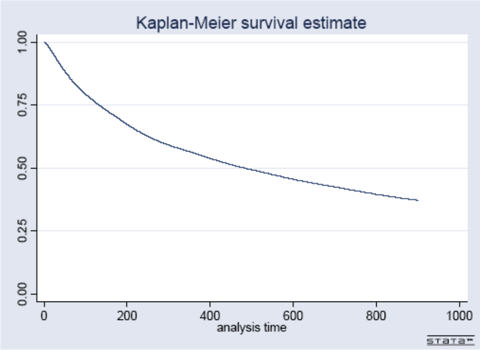



Figure: Example of a Kaplan-Meier estimate of the Survival function: Unemployment duration in days censored after 900 days (French data pooled over 2001-4; source: Marc Gurgand).

# Parametric models

## The proportional hazard model

In a *reduced form approach*, one would like to relate the hazard to

- Explanatory variables (which should be exogenous)
    - Socio-demographic variables (education, gender, age,...)
    - "Policy parameters" (Unemployment benefit level,...)

  Denote all explanatory variables by a vector $X$
  (not to be confounded with the reservation wage $x$!).
- Unemployment duration $t$.

The most commonly used empirical specification is the so called "**proportional hazard model**":

$$h(t; X) = h_0(t)\exp(X'\beta) \tag{13}$$

Why "proportional"? Because any change in a component of $X$ shifts the "baseline hazard", $h_0(t) \geq 0$, without changing its shape.

$h_0(t)$ refers to the "**baseline hazard**"
Possible specifications:

- Parametric specifications like the Weibull (to be avoided: generally not flexible enough).
- Piecewise constant: The time axis is divided into $m$ intervals $[t_l, t_{l+1}[$ (with $0 = t_1 < t_2 < ... < t_m$) and the baseline hazard is constant on each interval = Much more flexible.

In such a specification the parameters $\beta$ can be interpreted as the proportional effect on the hazard of a unit increase in $X$:

$$\beta = \frac{\partial \ln h(t; X)}{\partial X} \tag{14}$$

If the explanatory variables are expressed in logarithms, $\beta$ can be interpreted as an elasticity.

# Dealing with methodological problems

Consider a sample of $N$ spells: $\{t_i, X_i\}_{i=1,\dots N}$.
If the hazard was time-invariant, we could specify $h(t) \equiv \phi = \exp(X'\beta)$.
By $\mathbb{E}(T) = 1/\phi$, and postulating that realizations, $t_i$, of the duration in a sample verify $t_i = \mathbb{E}(T) \cdot \varepsilon_i'$, we would obtain:

$$\ln t_i = -X_i'\beta + \varepsilon_i \tag{15}$$

*Problems:*

1. How to treat censored observations?
2. What if the explanatory variables vary over unemployment duration ($X_i(t)$)?
3. In (15), $t_i = \mathbb{E}(T) \cdot \varepsilon_i'$ is an *ad hoc* assumption. We do not take explicitly into account that $T$ follows an exponential distribution. In maximum likelihood methods we can impose such a distribution and the estimator will therefore be more precise.

# Solutions

1. *Right censored* observations. The contribution of such observations to the likelihood function is simply the probability that they survive in unemployment up to the duration they are censored, denoted $t_c$:

$$\overline{G}(t_c) = \exp[-\int_0^{t_c} h(s; X(s))ds] \tag{16}$$

2. *Left censoring* is a difficult problem. It can be solved, but the solutions proposed until now are typically very sensitive to the assumptions made. For more discussion on this issue the reader is referred to Lancaster (1990).
3. *Time-varying* explanatory variables can be easily taken into account if one specifies the model in terms of the hazard rate: e.g. $h(t; X(t)) = h_0(t)\exp[X(t)'\beta]$.
   Attention: time-varying explanatory variables can be endogenous (caused by unemployment duration)

# The likelihood function

## Flow sample

In a sample of $N$ "fresh" spells we have two kinds of observations:

1. completed spells (denoted below by $\delta = 1$)
2. and right-censored spells (denoted below by $\delta = 0$).

Contribution to the likelihood function:

- The contribution of a completed spell is the density of unemployment duration. Remembering (8), the density of a completed duration $t_i$ for individual $i$:

$$g(t_i) = h(t_i; X_i(t_i))\overline{G}(t_i) = h(t_i; X_i(t_i)) \exp[-\int_0^{t_i} h(s; X_i(s))ds] \tag{17}$$

- The contribution to the likelihood of a right-censored spell is given by (16).

In a sample mixing completed and right-censored spells, the log-likelihood is:

$$\ln L = \sum_{i=1}^{N} \delta_i \ln\left[h(t_i; X_i(t_i))\right] - \int_0^{t_i} h(s; X_i(s))ds \tag{18}$$

From (18), the likelihood function is completely specified once the hazard rate has been specified:

- In the case of a proportional model, $h(t_i; X_i(t_i)) = h_0(t_i)\exp[X_i(t_i)'\beta]$
- In the case of the structural approach, the specification of the hazard would come directly from the theory (and the formula(s) for the optimally chosen decision variables would be included).

Next the log-likelihood needs to be maximized w.r.t. the parameters.

“Fully parametric models (...) produce inconsistent parameter estimates if any part of the parametric model is misspecified” (Cameron and Triverdi, 2005, p.592)

In particular the baseline hazard $h_0(t)$ should be flexible enough. Then, the estimation of the model becomes more complex.

The so-called “Cox Proportional Hazard Model" defines a partial likelihood function where under certain conditions the baseline hazard disappears. For more details, see e.g. Chap. 17 of Cameron and Triverdi (2005).

## Exercise (3)

*A random sample of N fresh unemployment spells is followed through time until a given finite calendar time. Index i designates a spell in this sample. Let* $\delta_i = 1$ *if the observation is NOT censored and zero otherwise. Let t denote unemployment duration (*$t = 0$ *at the beginning of spell). Time is continuous. Individual i in this sample has time-invariant observable characteristics* $X_i$*. The researcher assumes a proportional hazard rate model. Moreover, a Weibull specification is assumed for the baseline hazard rate* $h_0(t)$*. Hence, the hazard rate out of unemployment at duration t with observables X is assumed to be:*

$$h(t; X) = \alpha t^{\alpha-1} \exp(X'\beta), \;\; \alpha > 0.$$

*Produce the log-likelihood function in the case of this sample under the above specification. Do not only write formulas: Add at least a few words to explain what you are doing.*

# Unobserved Heterogeneity and Duration Dependence

Stylized fact: Following a cohort of unemployed workers from the moment they have entered unemployment, the rate at which unemployment is left over duration exhibits “negative duration dependence”.

BRUCE D. MEYER

TABLE II

FAILURES, CENSORINGS, AND THE KAPLAN-MEIER EMPIRICAL HAZARD[a]

| Week $t$ | Risk set $R_t$ | Failures $D_t$ | Censorings $C_t$ | Hazard $H_t$ | Standard error |
|---|---|---|---|---|---|
| 1 | 3365 | 277 | 0 | .08232 | .0047 |
| 2 | 3062 | 203 | 26 | .06630 | .0045 |
| 3 | 2832 | 159 | 27 | .05614 | .0043 |
| 4 | 2657 | 161 | 16 | .06059 | .0046 |
| 5 | 2458 | 123 | 38 | .05004 | .0044 |
| 6 | 2271 | 112 | 64 | .04932 | .0045 |
| 7 | 2112 | 88 | 47 | .04167 | .0043 |
| 8 | 1984 | 82 | 40 | .04133 | .0045 |

“Negative duration dependence” seems to contradict with job search theory predictions:

- In the stationary case the exit rate is constant
- In the non-stationary model positive duration dependence is easier to predict than negative

# Two responses to this problem

(1) Negative duration dependence could be "**true**":

a) Job offers arrive at a slower rate and the mean of the wage offer distribution shifts to the left, because of loss in human capital;
b) Firms, in their recruitment decision, may rank unemployed workers according to unemployment duration. Thereby they lower the job arrival rate and the hazard with unemployment duration.
c) Network effects: As duration increases, the likelihood that the unemployed's connections are unemployed increases (Calvó-Armengol and Jackson, 2004).

+ the reaction of the unemployed ("discouragement", lower search intensity).

(2) The negative duration dependence could, however, be "**spurious**" resulting from a sorting process induced by "**unobserved heterogeneity**" of workers. To see this take the following example:

Assume that the workers entering unemployment consist of two groups:

(1) 50 % consist of workers for whom the hazard is constant at 10 %.

(2) 50 % consist of workers for whom the hazard is constant at 20 %.

*Even if the hazard rate of each of these two groups separately is constant*, the hazard of the population combining these two groups will exhibit negative duration dependence. Indeed, consider a group of 10.000 workers entering unemployment:

| # months | # gr. 1 (share) | # gr. 2 (share) | total | exit rate of total |
|---|---|---|---|---|
| 0 | 5.000 (50%) | 5.000 (50%) | 10.000 | - |
| 1 | 4.500 (53%) | 4.000 (47%) | 8.500 | $\frac{1.500}{10.000} = 15\%$ |
| 2 | 4.050 (56%) | 3.200 (44%) | 7.250 | $\frac{450+800}{8.500} = 14.7\%$ |
| 3 | 3.645 (59%) | 2.560 (41%) | 6.205 | $\frac{1.045}{7.250} = 14.4\%$ |
| 4 | 3.280 | 2.048 | $\ldots$ | $\ldots$ |
| $\vdots$ | | | 1.998 | |
| 12 | 1412 (80%) | 344 (20%) | 1.756 | $\frac{242}{1.998} = 12.1\%$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| $\infty$ | (100)% | (0)% | | 10% |

There is a selection process going on:

- Type 2 workers leave unemployment more rapidly than the type 1 workers
- $\Rightarrow$ The share of type 1 workers in the population of survivors in unemployment, increases with duration
- $\Rightarrow$ Since type 1 workers have lower exit rates, the aggregate exit rate decreases
  Reason = a change in composition only
- Such duration dependence is clearly “spurious”.

Consequently, if one does not take unobserved heterogeneity into account, estimates of duration dependence are biased downwards.

*Even if one accounts for observed differences, some residual unobserved heterogeneity is always likely.*

Moreover, ignoring unobserved heterogeneity will also bias the parameters $\beta$ affecting the explanatory variables $X$ of the hazard, *even if these unobserved factors are NOT correlated with the observed explanatory variables*.

Intuition: Take education which typically affects the hazard from unemployment to employment positively ($\beta > 0$).
As duration lengthens, the more educated who remain unemployed have poor unobserved characteristics.
Ignoring unobserved heterogeneity $\Rightarrow$ confounding the impact of education and the one of poor unobserved characteristics $\Rightarrow$ Underestimation of the effect of education.

*The problem of neglecting unobserved factors is therefore more serious in duration analysis as compared to standard regression analysis!*

Fortunately, we can account for unobserved heterogeneity if we are willing to make some identifying assumption. Mainly:

- if the hazard conditional on *the unobserved heterogeneity term* $v$ is proportional, i.e. if one assumes a "**Mixed proportional hazard model**":

$$h(t; X, v) = h_0\,(t) \exp\left(X'\beta\right) v \tag{19}$$

  for $v \geq 0$.

Then, (without proof) the distribution of unobserved heterogeneity can be completely (non-parametrically) identified apart from a normalisation.

Consider a completed spell sampled from the flow into unemployment (completed duration $t$, observed characteristics $X$), the likelihood contribution will be:

$$\int_0^\infty h(t;X,v)\exp\left[-\int_0^t h(s;X,v)\,ds\right]d\mathcal{H}(v) \tag{20}$$

where $\mathcal{H}(v)$ is the CDF of $v$.

Standard approaches:

- Either specify for $v$ a Gamma distribution that gives a closed form for this integral
- Or take a discrete distribution, i.e. $v$ can take values ("mass points") $v_1, ..., v_k$ with probability $\pi_1, ...\pi_k$. [3]

[3] The number $k$ is determined by adding consecutively mass points as long as the Akaike Information Criterion decreases. See Gaure, Røed and Zhang (2007).

# Empirical Results

# 1. The Role of Individual Characteristics

In most estimations, the following characteristics are negatively correlated with the hazard rate from unemployment to employment:

- Low education level;
- Being a woman, in particular interacted with having young children;
- Being a foreigner or non-native (at least if the nationality or country of origin is “non-EU”);
- Poor knowledge of (national/foreign) languages;
- Living in a region with a high unemployment rate;

These results do not contradict the theoretical predictions of job-search theory.

The role of benefits and unemployment duration being discussed afterwards.

# 2. Effects of unemployment insurance

## Microeconometric evidence

How are these effects identified?

- The impact of UB can be estimated by comparing unemployment durations of different workers entitled to different levels of unemployment benefits ('UB').
  *Possible selection bias*:
  Example: More labor market experience $\Rightarrow$ Higher UB & exit rates $\Rightarrow$ if measure of labor market experience is imperfect, the negative impact of UB will be biased upward to zero.
- The more recent evidence exploits so-called "natural experiments" (or "quasi-experimental" data):
  Typically an (unanticipated) reform of the level (or the duration) of UB.
  See example below.

Effects of the level of unemployment benefits (UB) on unemployment duration:
The debate about the size of their impact is not closed at all!
Often: *Small effects, but consistent with the theory.*
Why "small"? Job search theory implicitly assumes that UB are a kind of unconditional income.

In reality benefits are conditional on job search and the willingness to accept job offers and the behavior of the unemployed is *to some extent* monitored by the UI agency.

$\Rightarrow$ The quite low elasticity of the hazard w.r.t. benefits might be partly explained by the risk of loosing benefits if one stops searching or become too choosy when UBs are increased.

For a recent survey on the effects of UB on the labor market see Tatsiramos and van Ours (2014).
See also `https://newsroom.iza.org/en/archive/opinion/how-much-unemployment-insurance-do-we-need/`.

# Evaluation ot an Austrian reform on August 1, 1989

Lalive, van Ours and Zweimüller (2006), summary by CCZ p. 282-295

| | | Age at the beginning of the spell | | | |
|---|---|---|---|---|---|
| | | Younger that 40 | | 40 and older | |
| | | Work experience | | Work experience | |
| | | Low | High | Low | High |
| Previous | $\leq$ 916€/month | eRR | eRR | eRR | eRR-PBD |
| Earnings | $>$ 916€/month | Control | Control | Control | ePBD |

Table: Changes in the replacement ratio (RR) and in potential benefit duration (PBD) on 1 August 1989 in Austria.
Note: Work experience “Low” refers to less than 6 out of previous 10 years and less than 9 out of previous 15 years work experience. Work experience “High” refers to worked more than 6 out of previous 10 and worked more than 9 out of previous 15 years. ePBD: eligible for increase in potential benefit duration; eRR: eligible for increase in replacement ratio; ePDB-RR: eligible for increase in potential duration benefits and in replacement ratio. Source: Lalive et al. (2006, Tab 2, p. 1018)

# Extraction of data

| id | dur | uncc | age |
|---|---|---|---|
| 1 | 0.712128 | 0 | 49.99863 |
| 2 | 0.712128 | 0 | 49.99863 |
| ... | ... | ... | ... |
| 189540 | 25.78669 | 1 | 36.21355 |
| ... | ... | ... | ... |

Table: Extraction of the dataset of Lalive et al (2006). id: identification number of unemployment spells; dur: duration of the unemployment spell (weeks); uncc equals 1 if the spell is censored and equals zero otherwise; age: age of the individual at the beginning of the unemployment spell.

◊ Magnitude of the changes:

| | Before August 1, 1989 | After August 1, 1989 |
|---|---|---|
| eRR | 41.4% | 47.3% |
| ePBD | 30 weeks | 39 or 52 weeks |

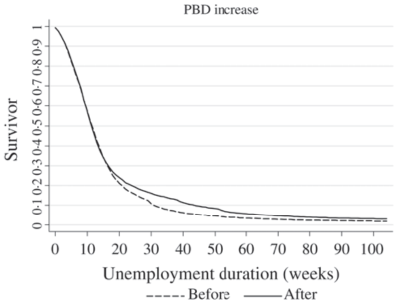
◊ Sample studied:

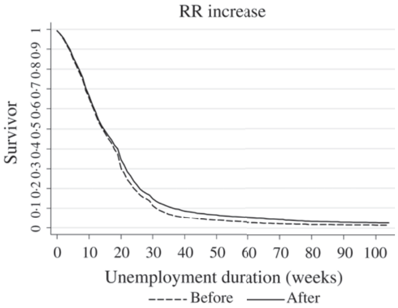
- A selection among all unemployment entrants in the window [1 August 1987; 31 July 1991], a period of time where macroeconomic conditions were stable in Austria (low risk of endogeneity of the reform);
- Age bracket (at entry in unemployment): 35 - 54;

◊ As they compare different cohorts and groups, a number of tests are conducted to convince the reader that the difference-in-differences approach is valid.

# Descriptive analysis

## Kaplan-Meier survivor functions



# Results of a statistical analysis

## Difference-in-differences approach focussed on ePBD only

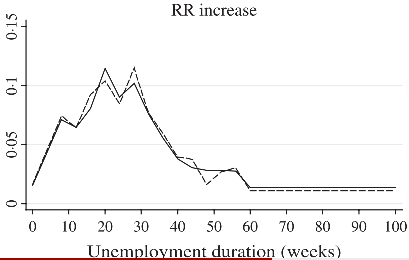
The hazard rate of individual *i* is specified as follows:

$$
\begin{aligned}
h(t_i; X_i) &= h_0(t_i)\exp(X_i'\beta) \\
h_0(t_i) &= \exp\left(\sum_{j=0}^{14} h_j \cdot \mathbb{1}\left(4j < t_i \leq 4(j+1)\right) + h_{15} \cdot \mathbb{1}(t_i > 60)\right) \\
h_j &= \beta_{0j} + \beta_{1j} \cdot \text{ePBD} + \beta_{2j} \cdot \text{A89} + \delta_j \cdot \text{ePBD} \cdot \text{A89},\; j = 0, .., 15.
\end{aligned}
$$

where actually the third line is more complex because of the presence of a group eRR and eRR-ePBD; ePBD = 1 if *i* belongs to the treated group (0 otherwise); $A89$ jumps from 0 to 1 when a spell enters the period after the reform has taken place; $X_i$ contains marital status, female, education, log(previous monthly income), recall status, blue collar, seasonal industry, manufacturing industry, time spent non-employed [history since the year 1972], tenure, and quarter of inflow.

# Estimated average treated and control hazard rates





# Simulated effects on the treated population

## Impact on expected duration in weeks

| | Treated | Control | Effect |
|---|---|---|---|
| No treatment | 16·91 | 16·91 | 0·00 |
| Change to one parameter | | | |
| PBD 30–39 weeks | 17·53 | 17·08 | 0·45 |
| PBD 30–52 weeks | 20·62 | 18·35 | 2·27 |
| RR increase | 20·97 | 20·60 | 0·38 |
| Change to two parameters | | | |
| PBD 30–39 and RR increase | 21·95 | 21·09 | 0·86 |
| PBD 30–52 and RR increase | 29·43 | 23·70 | 5·72 |

Note: The paper develops a sensitivity analysis not covered here. Some effects are larger with a Regression Discontinuity Design approach.

# Through which channels does UI play a role?

If there is any impact of the level of UB's on unemployment duration, it is mainly through its *impact on job search behaviour and less so on the reservation wage*:

- Research provides *limited* evidence suggesting that job offers are rarely rejected (see Eckstein and van den Berg, 2007).
  $\Rightarrow$ reservation wage $\approx$ the lower bound of the wage offer distribution, as predicted by the "equilibrium search model";
  & role of minimum wages (if enforced and binding).
- Differences in unemployment duration could then mainly reflect differences in job arrival rates, which themselves depend on search intensity.
  $\Rightarrow$ Different programs (counselling, monitoring of job search behavior & sanctions, compulsory "active programs" and re-employment bonuses) aiming at increasing the search intensity.

# Through which channels does UI play a role?

## Other effects (see Zweimüller, 2018 for an overview)

1. Higher UB or UB for a longer duration $\Rightarrow$ less pressure to find a new job quickly.
   Can this lead to a better match between job seekers and job vacancies and hence create longer lasting employment spells?
   - Yes : Tatsiramos (2009), Caliendo, Tatsiramos and Uhlendorff (2013) ;
   - No : Card, Chetty and Weber (2007), van Ours and Vodopivec (2008).

   Complex question: A more generous UI
   - Pushes reservation wages upwards $\Rightarrow$ Expected wages $\nearrow$;
   - Increases unemployment duration $\Rightarrow$ This can induce a negative shift the wage distribution (see “duration dependence” later on);

   See Nekoei and Weber (2017) and Marinescu and Skandalis (2021).

# Through which channels does UI play a role?

## Other effects

2. With borrowing constraints, higher UB increases cash on hand and consumption and it lowers pressure to find a job. According to Card, Chetty and Weber (2007) and Chetty (2008), this explains to a large extent the impact of UI on unemployment duration.
3. Positive impact of the generosity of the UI scheme on *entry* into unemployment (see Feldstein, 1978 and Lalive, van Ours and Zweimüller, 2011).
4. UI benefit variation in a given labor market can affect job search outcomes of those not eligible to this variation! See evidence of such “spillover effects” by Lalive, Landais and Zweimüller (2015).

# 3. Is there true duration dependence?

Econometric analyses that account for unobserved heterogeneity often reach diverging conclusion about **true duration dependence**:

- According to van den Berg and van Ours (1996) about U.S. unemployment data for the period 1967-91, "duration dependent stigma effects related to unemployment durations are dominant for white workers, but not for black workers".
- van den Berg and van Ours (1994): "For British male individuals we found strong genuine negative duration dependence, i.e. a decline of the exit rate over duration for a given individual. For French individuals there is no strong duration dependence during the first year, while for Dutch individuals there is non-monotonous (inverse-U shaped) duration dependence over the first three quarters of unemployment."
- Using US data (CPS 2003-10), Abraham, Haltiwanger, Sandusky and Spletzer (2016) provide evidence of true negative duration dependence.

Different approach by Kroft, Lange and Notowidigdo (2013):

- They submit 12,000 fictitious résumés to 3,000 real job vacancies;
- The unemployment spell length (1 to 36 months) is orthogonal to all of the other characteristics of the resume;
- They track "callbacks" from employers to each submitted résumé;
- Main results:
  1. "The average callback rate sharply declines during the first eight months of unemployment and then it stabilizes." It "falls from roughly 7% to 4%." (p. 1125)
  2. "Duration dependence is significantly stronger when the local labor market is tight." (p. 1125) "This result is consistent with the prediction of a broad class of screening models in which employers use the length of the unemployment spell as a signal of unobserved productivity and recognize that this signal is less informative in weak labor markets." (p. 1126)

Importance of these conclusions discussed by Jarosch and Pilossoph (2018).

# Critique of the job-search approach: Can the job-search model fit wage dispersion and unemployment exit rates?

# An empirical critique of the whole job search approach

Hornstein, Krusell and Violante (2011): The basic job-search model, once properly calibrated, generates very low wage differentials among ex-ante similar workers.

> *"The key reason for this finding is the short duration of unemployment spells in the [US] data. Intuitively, given that unemployed workers choose to take jobs quickly, they must not perceive a high option value of waiting for better job offers. In the basic model, this option value is determined precisely by wage dispersion. Taking workers' flow data at face value, one can escape the conclusion of a very low mean-min ratio only if workers are implausibly impatient or have an implausibly low (indeed negative) value of non-market time." (p. 2874)*

# The critique of Hornstein, Krusell and Violante (2011)

- In the basic model of Section 1 (job-search1.pdf), the reservation wage equation can be rewritten as:

$$x = \rho\overline{w} + \frac{\phi}{r+q}(\overline{w} - x)$$

  where $\overline{w} \equiv E(w \mid w \geq x)$, $\phi$ is the unemployment exit rate and the *net* instantaneous income in unemployment $z$ is assumed proportional to $\overline{w}$: $z = \rho\overline{w}$.
- From this, once the parameters are calibrated, the "mean-min ratio" $\overline{w}/x$ verifies

$$\frac{\overline{w}}{x} = \frac{1 + \frac{\phi}{r+q}}{\rho + \frac{\phi}{r+q}} \approx 1.05(\text{US}); 1.10(\text{EU}).$$

$\rightarrow$ Negligible departure from 'the law of one price'?

# Reply to this critique

- Remember that $z = b - c$ in the basic model where
  - $c =$ the out-of-pocket costs of job search + opportunity cost of time devoted to search
  - $b =$ the monetary value of domestic production and “leisure” net of losses due to unemployment *per se* (stigma, low self-esteem) + unemployment benefits (if any)
  - Why would $z$ be necessarily $> 0$ for all groups? ($\rho < 0 \Rightarrow \overline{w}/x \nearrow$ )
- Extending the framework to on-the-job search can generate reasonable wage differentials if the job arrival rate in employment is high enough (since this lowers the reservation wage).

# Reply to this critique

## Continued

- Other models lead to higher mean-min ratios. See e.g.
  - Burdett and Mortensen (1998) (with firms' competition in wages to attract workers; discussed later on) or
  - Burdett, Carrillo-Tudela and Coles (2011) (with learning by doing).

Final note:
For an introduction to duration analysis with Stata, see:
`https://www.iser.essex.ac.uk/resources/survival-analysis-with-stata`

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